Implementations of the Navy Coupled Ocean Data Assimilation System at the Naval Oceanographic Office

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Abstract— **The Naval Oceanographic Office uses the Navy Coupled Ocean Data Assimilation (NCODA) system to perform data assimilation for ocean modeling. Currently the system uses a 3D multivariate optimum interpolation (3D MVOI) algorithm to produce outputs of temperature, salinity, geopotential, and u/v velocity. NCODA is run in a stand–alone mode to support automated ocean data quality control (NCODA OcnQC) and to test software updates. NCODA is also coupled with the Regional/Global Navy Coastal Ocean Model (RNCOM/GNCOM). The RNCOM/NCODA system is being used as part of an Adaptive Sampling and Prediction (ASAP) pre–operational project, that makes use of the Ensemble Transform (ET) and Ensemble Transform Kalman Filter (ET KF) applied to ensemble runs of the RNCOM. The ET KF is used to predict the posterior error covariances resulting from possible profile measurements. These results aid in predicting the impact of ocean observations on the future analysis, and thus allow the direction of limited assets to areas that will have the maximum gain (for applications such as ocean acoustics). A review of these systems will be given as well as examples of the metrics used for the RNCOM/NCODA system, ensemble modeling, and ASAP.**

I. NCODA

The Naval Oceanographic Office uses the Navy Coupled Ocean Data Assimilation (NCODA) system [1] to perform data assimilation for ocean modeling. This system is implemented on the supercomputer configuration of the Navy DoD Supercomputing Resource Center (Navy DSRC). The NCODA analysis is running in both a (1) stand–alone mode (NCODA-SA) to support real–time automated ocean data quality control (NCODA OcnQC) and to test software updates, as well as (2) coupled with the Global Navy Coastal Ocean Model (GNCOM) (GNCOM/NCODA) and Regional Navy Coastal Ocean Model (RNCOM) (RNCOM/NCODA).

The NCODA system consists of a frontend ocean data quality control (NCODA OcnQC) program that feeds an analysis program (NCODA Analysis). Currently the analysis system is based upon a 3D multivariate optimum interpolation (3D MVOI) algorithm [2] to produce 3D output fields of temperature, salinity, geopotential, and geostrophic u/v velocity (T, S, Φ, U, V). NCODA can be used for global or regional applications and is relocatable with the ability to have multi–scale analysis nests (with successively higher resolution grids in a 3:1 nest ratio).

A. NCODA Implementation

The NCODA OcnQC is run on a 6–hour schedule for feeding the NCODA-SA, RNCOM/NCODA, and GNCOM/NCODA systems. Part of NCODA OcnQC is the running of 2D OI analyses of sea–surface temperature (SST) and sea ice in order to QC SST and sea ice observations. These are performed in the arctic on a 9 km polar stereographic grid and globally on a 9–12 km Mercator grid (midlatitude versus equatorial grid spacing). The output of a previous NCODA Analysis can also be used as a background field for QC of *in situ* profile observations.

The NCODA Analysis (with and without coupling with an ocean model) is run on a 24 hour schedule. The global analysis is performed on a 12–18 km Mercator grid (1/6°), with future plans of 9–13.5 km grid (1/8°). Regional NCODAs can be run on a variety of grids, but in general are either on a Mercator or spherical projection at a nominal 3 km grid resolution.

The data and process flow of the NCODA system can be seen in figure 1. The raw observations are processed by the NCODA OcnQC and assigned "probability of error" (POE) values. The data and its associated POE values input to the NCODA Analysis. Within the analysis the POE values are used to omit errant data and are also used in assigning weights to the data. The output of the analysis is given to an ocean model either as 3D fields

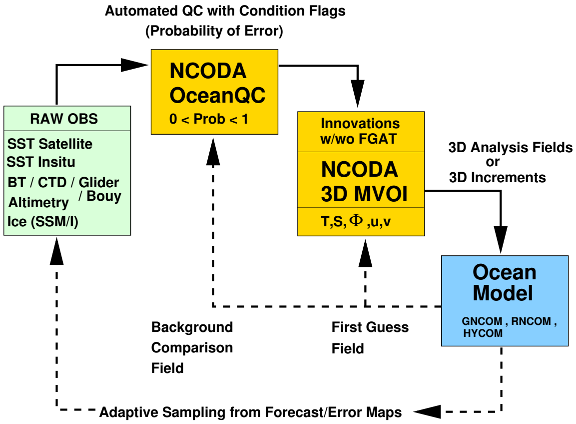

Fig. 1. RNCOM/NCODA data flowchart.

or 3D increments. The ocean model assimilates these fields and produces forecast(s) that can then be used for future quality control tests or for other purposes such as adaptive sampling. Additional details of this flowchart will be explained below.

B. NCODA Runtimes

Part of the NCODA implementation process was to determine how many processors on the Navy DSRC were optimal for running NCODA [3]. On the DSRC system, each processor consisted of 8 CPUs. Tests were done for three CPU configurations to determine how the runtimes responded. The NCODA code is a mixture of serial and parallel code. As such there is a limit to how fast the code can be run. In figure 2 an example is shown of the runtimes for the NCODA-SA Global3D region with 8 processors. Runtimes are affected by (1) the size of state vector (proportional to the number of grid points), (2) the number of CPUs, and (3) the number of input observations.

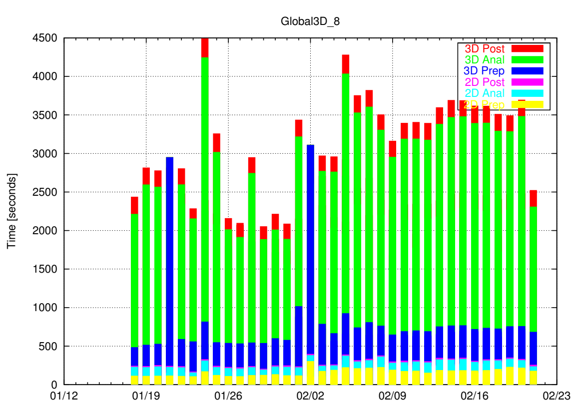

Fig. 2. NCODA Analysis Global3D 8 processors.

Each NCODA region runs a combination of 2D and 3D serial and parallel processes. The preprocessing and postprocessing is serial, while the analysis has some parallel code. The 2D processes involve 2D OI of SST and SSHA. The 3D processes are concerned with the 3D MVOI analysis and its results. In figure 2 the 2D preparation is shown in yellow, 2D analysis in cyan, 2D postprocessing in magenta, 3D preparation in blue, 3D analysis in green, and 3D postprocessing in red. It is readily apparent that the majority of the runtime is spent in the 3D MVOI.

The following table summarizes the results for 8, 16, and 32 processors (64, 128, 256 CPUs). Shown is the average *analysis* runtime, not including pre/post–processing (the pre/post–processing is serial, while the analysis is partly parallelized).

3D Global Analysis Runtime Improvement

CPU	Runtime (minutes)	Decrease (minutes)
64	40	–
128	25	15
256	20	5

The speedup of the NCODA OI/MVOI analysis using multiple processors in parallel is limited by the time needed for executing the serial portion of the program and how efficient the parallelizing is. Amdahl's law [4] can be used to find the maximum expected improvement to the NCODA runtime when only part of the system can be improved.

Write Amdahl's Law as $SPEEDUP = \frac{1}{1-P}$, where $SPEEDUP$ is the potential program speedup if a P fraction of code can be parallelized. The results for the runtimes of Global2D OI and Global3D MVOI are shown in the following table. Gains for the second doubling are half of the first, perhaps because (1) the parallelizing could be improved and (2) the scalability of parallelizing is reaching its limit. Based upon the results shown in the these two tables and the current configuration limitations, generally the NCODA 2D is run with 32 or 64 CPUs, while the NCODA 3D is run with 128 CPUs.

REGION	Δ CPU	Speedup	Parallelizable
Global2D	64 to 128	1.75	43 %
Global2D	128 to 256	1.28	23 %
Global3D	64 to 128	1.62	38 %
Global3D	128 to 256	1.26	21 %

C. NCODA OcnQC

Quality control (QC) of oceanic observations is an important requirement for the running of the NCODA system [5]. Errant data must be flagged, similar data must be pooled, overly abundant data must be thinned, and duplicate data must be eliminated. In this process, valid but extreme data values are hopefully retained. The ultimate goal of the QC is to feed "clean" data to the analysis algorithm so that the output of the analysis will not be misleading and the possibility of making wrong decisions is reduced or eliminated.

QC of profile data is of particular importance due to the need for information at depth and the small number of profiles relative to other data types. A sequence of gross–error data checks are performed including valid–value range tests, land–sea checks (being implemented), and location (speed) tests (being implemented). A series of instrumentation error checks are then performed, such as a sensor drift check. Cross validation checks are performed to ensure the consistency of observations within and between analysis variables. In the within–variable consistency check, an OI analysis is performed at the profile location, based upon nearby valid data (and excluding the datum being checked).

The last (and most important) check before the analysis is the background–field checks. The background field checks can involve climatology, global and regional analyses, or short–term forecasts. The background fields and background error fields closest in time to the datum are interpolated to its position. The probability of an erroneous value (the "probability of error" or POE) is calculated from the anomalies of the background fields with respect to the datum [5].

Figure 3 displays several of the background fields used in computing the POE, which is computed both as an overall value and a function of depth.

A final QC check is done within the analysis to remove any data that have passed the previous checks. The normalized innovation corresponding to the data is tested against the analysis background, and if it is beyond a predefined number of standard deviations, the data (innovation) is rejected. This assumes that the background error covariance ($\mathbf{P}_b$) and observation error covariance ($\mathbf{R}$) are reasonably known. It is best to use a high tolerance value, and four standard deviations is commonly specified.

D. NCODA Analysis

The NCODA 3D MVOI algorithm is formulated in observation space as follows (with definitions in the following table):

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{P}_b\mathbf{H}^{\mathrm{T}}[\mathbf{H}\mathbf{P}_b\mathbf{H}^{\mathrm{T}} + \mathbf{R}]^{-1}[\mathbf{y} - \boldsymbol{H}(\mathbf{x}_b)]$$

$\mathbf{y}$	Observation Vector
$\mathbf{x}_b$	Background Vector
$\mathbf{x}_a$	Analysis Vector
$\boldsymbol{H}, \mathbf{H}$	Forward Operator, Matrix[1]
$\mathbf{R}$	Observation Error Covariance
$\mathbf{P}_b$	Background Error Covariance
$\mathbf{y} - \boldsymbol{H}(\mathbf{x}_b)$	Innovation Vector
$\mathbf{y} - \boldsymbol{H}(\mathbf{x}_a)$	Residual Vector
$\mathbf{x}_a - \mathbf{x}_b$	Increment Vector

[1] The Forward Operator $\boldsymbol{H}$ is a method of converting a forecast model variable to an observed variable. For NCODA the observations and forecast variables are the same, and $\boldsymbol{H}$ reduces to a spatial interpolation.

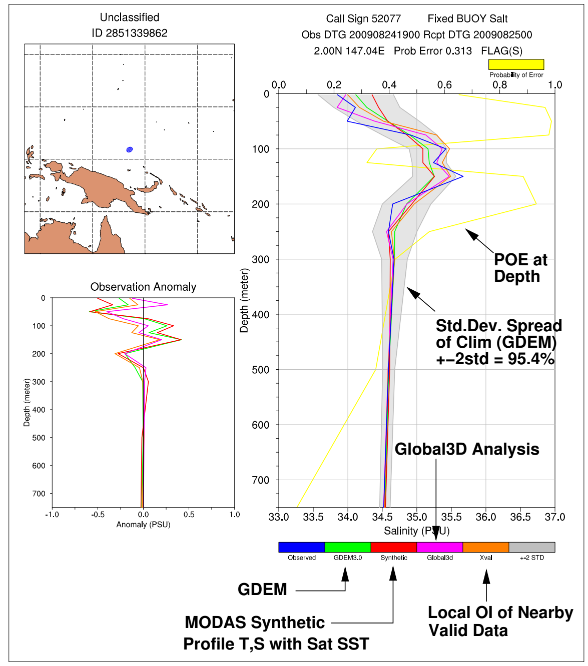

Fig. 3. NCODA OcnQC profile plot. Displayed are the profile and the anomaly with respect to the profile. The "probability of error" (POE) is given both as a function of depth (yellow curve) and as an overall value.

The analysis increment is equivalently defined by $\mathbf{P}_b\mathbf{H}^{\mathrm{T}}[\mathbf{H}\mathbf{P}_b\mathbf{H}^{\mathrm{T}} + \mathbf{R}]^{-1}[\mathbf{y} - \boldsymbol{H}(\mathbf{x}_b)]$. The quantity $\mathbf{P}_b\mathbf{H}^{\mathrm{T}}[\mathbf{H}\mathbf{P}_b\mathbf{H}^{\mathrm{T}} + \mathbf{R}]^{-1}$ is the weight matrix (also commonly called the Kalman gain matrix). Within the 3D MVOI algorithm, the variables are constrained such that hydrostatic balance and geostrophy are maintained.

The solution of the MVOI equation is carried out by an overlapping volume approach [6]. Eight volume solutions are computed for each analysis grid point, with each one weighted by its distance from the volume center. The volume sizes are a function of the local correlation length–scale, such that eight correlation length–scales are used. Smooth analysis increments result from this combinition of overlapping volumes and multiple correlation length–scales within a volume.

The background and observation error covariances ($\mathbf{P}_b$ and $\mathbf{R}$) are separated into an error variance and a correlation [1]. The correlations are further separated into horizontal (C_h) and vertical (C_v) components. A tunable flow–dependent correlation is also introduced at this point (C_f). The total background error correlation is then represented as

$$C_b = C_h C_v C_f$$

The default horizontal correlation length–scale used by NCODA is the (location–dependent) first order baroclinic Rossby radius of deformation (see figure 4). This horizontal correlation length–scale can be either scaled or replaced by user–preferred values (such as those produced by the ensemble method in section IV).

The vertical correlation length–scales can (1) be constant, (2) monotonically increase or decrease with depth, or (3) vary with the background vertical density gradient. The third option allows the vertical correlation length–scale to be large when the water column stratification is weak, or small when the stratification is strong. It may be represented as

$$h_v = \rho_s / (\partial \rho / \partial z)$$

where h_v is the resulting vertical correlation length–scale, ρ_s is a "change in density stability criterion" (which defines a well–mixed layer), and $\partial \rho / \partial z$ is the vertical density gradient.

The flow–dependent correlation is computed from a scaling of the geopotential height difference between two locations. This flow–dependence affects both the horizontal and vertical correlations. Theoretically other fields that give a good indication of the flow–field could also be used.

The NCODA covariances can thus be "tuned" for regional applications by using regionally dependent (1) horizontal and vertical correlation length–scales, and (2) flow–dependence.

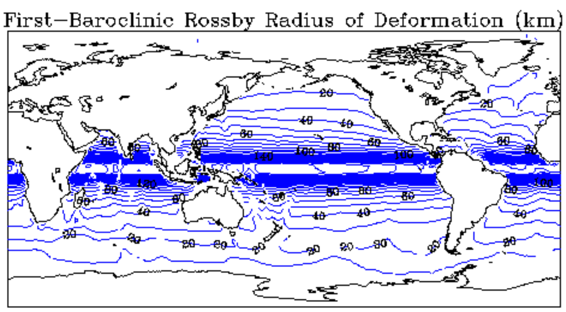

Fig. 4. NCODA's location–dependent default horizontal correlation length–scale based on the first order baroclinic Rossby radius of deformation (figure courtesy of Jim Cummings).

An important part of the NCODA system is keeping track of the data and analysis mismatches to aid in computing a reliable estimate of the background errors. To facilitate this, there are three items of particular interest for which NCODA keeps a time history: the *data error*, the *predicted background error*, and an *innovation error* check (the innovation error check will be covered in section III-A).

The *data error* is a weighted running sum of squares from a time history of the analyzed increment fields. These are used to compute the background errors of the appropriate analysis variables.

The *predicted background error* is computed from a weighted time history of the analyzed increment fields, the data error fields, and the climatological or model error field. It is also referred to as a prediction or forecast error, since it is the error attached to the MVOI background field, which is commonly obtained from the forecast of an ocean model. The predicted background error (e_b) is computed by

$$e_b^2 = \beta \cdot ((\sum_{k=1}^{n} w_k (x_a - x_b)_k^2) + w_{n+1} \langle (x_a - x_b)^2 \rangle) + (1 - \beta) \cdot \sigma_b^2$$

with $\beta = exp(-\tau/\tau_c)^2$. τ is the age of the data. τ_c adjusts the rate at which the background error approaches the climatological or model error in the absence of observations. Time scales range from $\approx$10 days for surface– and mixed–layer variables to $\approx$30 days for variables at depth. n is the number of days in the past to use in computing the weighted summation (with k being the day index). w_k are weight functions defined by $w_k = (1 - \phi)^{k-1}$, with ϕ an adjustable tuning factor. The brackets $\langle \ldots \rangle$ represent a long–term mean increment vector. σ_b is the expected error in the analysis variable in the long–term absence of observations.

NCODA keeps track of the observation age (at all model grid points) used in computing the predicted background error. An update to any variable in the MVOI analysis (from an observation) results in an update to the observation age of all related variables. Figure 5 is an example of the observation age at 200 meter in the North Atlantic. Since updates at depth occur only from *in situ* profiles or synthetic bathythermographs, grid points at depth are updated less often than those near the surface. However, there is also less oceanic activity at depth, and so the fields at depth are closer to climatology than those at the surface. An example of the resulting predicted background error for SST is shown in figure 6, with the largest errors occurring mostly in the regions of largest mesoscale activity.

Prior to the 3D MVOI, 2D OI analyses of sea–surface temperature (SST), sea–surface height anomaly (SSHA), and sea ice are performed. The 2D OI preprocessing of the SST data is done to reduce the runtime of the 3D MVOI. The 2D OI of the SSHA data is done in order to determine at which locations to produce synthetic bathythermographs as a means of communicating the ocean topographic information to the subsurface.

Before the SST data are passed to the 3D MVOI (upper–left plot in figure 7), they are preprocessed by a 2D OI. The output of the 2D OI is an SST increment (lower–left plot in figure 7) to which a threshold is applied and then a subsampling is performed (upper–right plot in figure 7). The resulting SST data are then passed on to the 3D MVOI. The resulting temperature increment at the surface (lower–right plot in figure 7) is seen to be almost identical to the SST increment in which all the SST data were used. This preprocessing results in a very large time savings in running the 3D MVOI.

An important part of NCODA is the transfer of oceanic topographic information to the subsurface. This is done by means of synthetic bathythermographic (BT) profiles. These profiles can be created by two methods: Cooper/Haines [7], and the Modular Ocean Data Assimilation System (MODAS) [8].

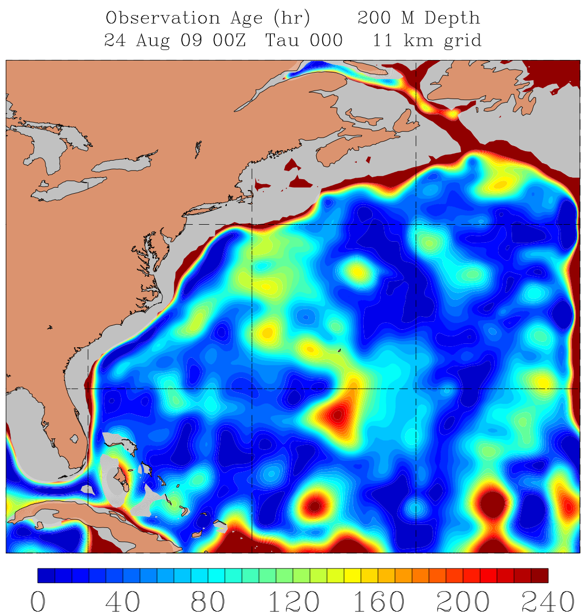

Fig. 5. An example of the "observation age" variable (at 200–meters) which NCODA uses to determine how much to relax a variable to climatological values. The observation age (at a grid point) is affected by updates to any of the related MVOI variables.

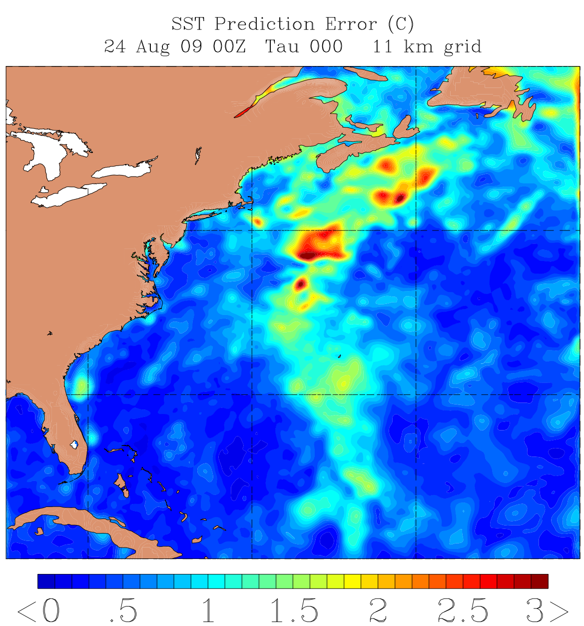

Fig. 6. An example of the "predicted background error" for SST.

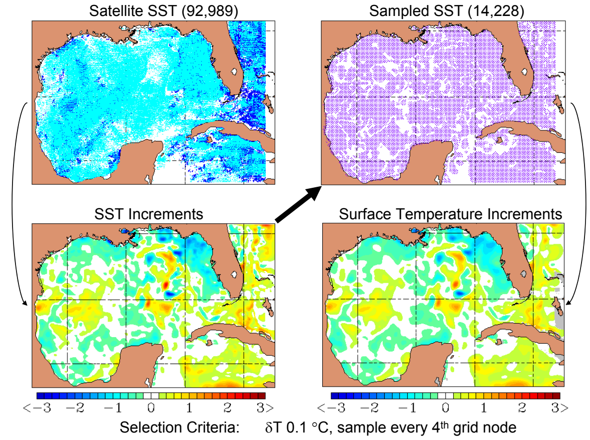

Fig. 7. Prior to the 3D MVOI of the NCODA Analysis, the original SST data are passed through a 2D OI that thresholds and subsamples it (figure courtesy of Jim Cummings).

The Cooper/Haines method ("direct method") needs an ocean forecast model. It adjusts the forecast density profile to be consistent with the change in SSHA (as measured by the altimeters). The temperature and salinity are computed simultaneously, and the water mass properties on subsurface isopycnals are conserved. Observation errors are computed from prior estimates and/or the analysis error variance plus the residual error from an iterative fit of the density adjustment.

The MODAS method is independent of an ocean forecast model. It computes temperature at depth from stored regressions (empirical orthogonal functions (EOFs)) between anomalies of climatological temperature and dynamic height. Salinity values are computed from climatological relationships between temperature and salinity. Observation errors are computed from prior estimates and/or the regression residuals.

Note that both methods generate temperature and salinity at depth using SSHA and SST predictor variables. A strong point of the Cooper/Haines method is that it does not introduce spurious water masses into the model. However, it cannot correct for long–term drift of water mass characteristics in the model. Given a good ocean forecast model, the Cooper/Haines method may be preferred [1]. The RNCOM/NCODA system uses the MODAS method at this time. When NCODA is run in stand–alone mode, the MODAS method is the only applicable option.

Both methods make synthetic BTs at locations determined by a 2D OI of SSHA prior to the 3D MVOI. Figure 8 shows an example of an SSHA increment. At locations where the absolute value of the increment is larger than a preset "noise" value (for example 2.0 centimeters), a cross–hatched subsampling will be performed (see figure 9). The resulting grid spacing is also adjustable. By means of these two parameters (along with the correlation length–scales) the influence of the altimetry can be adjusted.

II. NCODA Coupled with GNCOM

The Global Navy Coastal Ocean Model (GNCOM) [9] makes use of several ocean models and data assimilation systems to accomplish its prediction of ocean forecasts. These include the Global Navy Layered Ocean Model (GNLOM) [10], the 2D OI capability of MODAS [11], the 3D OI capability of MODAS [8], and the MVOI method of NCODA [1]. The relationship of these systems is shown in figure 10.

GNCOM encompasses the open ocean to 5 m depth

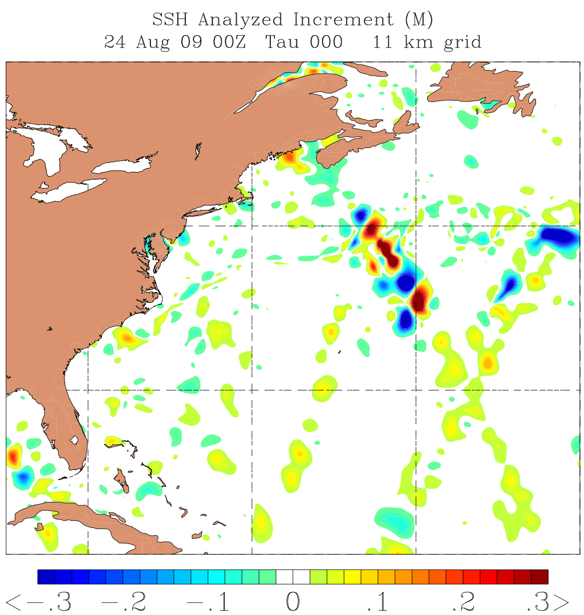

Fig. 8. An example of a 2D SSHA increment output from the 2D OI preprocessing of the NCODA Analysis .

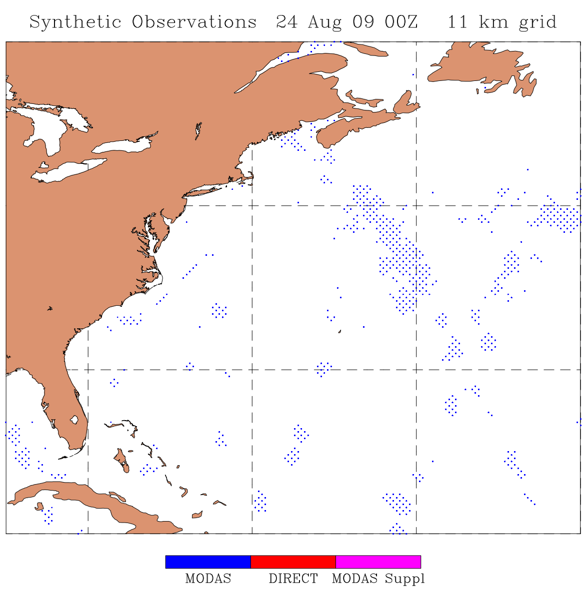

Fig. 9. After applying a height threshold test to the 2D SSHA increment, a grid of locations is generated, which will dictate where synthetic BTs will be created for input to the 3D MVOI analysis.

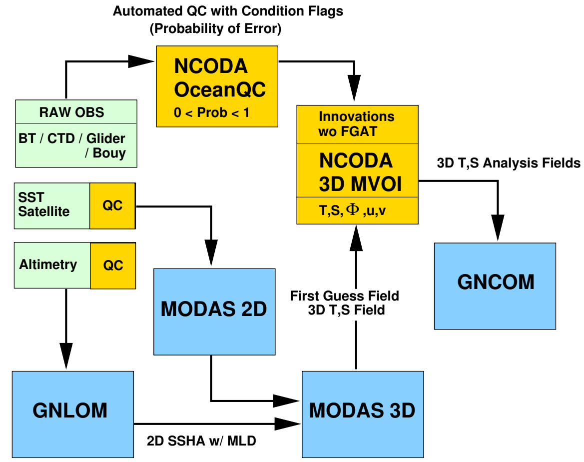

Fig. 10. GNCOM/NCODA data flowchart.

in a curvilinear global grid with 1/8 degree grid spacing at 45 N, extending from 80 S to a complete arctic cap with grid singularities mapped into Canada and Russia [12]. The model employs 40 vertical Sigma/Z levels, with Sigma in the upper ocean and coastal regions, and Z in the deeper ocean. The real–time systems (GNCOM and GNLOM) are forced with the global 1/2° Navy Operational Global Atmospheric Prediction System (NOGAPS) [13].

The input observations to GNCOM follow two different processing paths, with the result of each path producing 3D temperature and salinity profiles. Satellite SST are processed by the 2D OI of MODAS 2D. Altimetry is input to GNLOM, which outputs 2D fields of SSHA and mixed layer depth (MLD). These are combined with the 2D SST output of MODAS 2D to form the inputs to MODAS 3D. MODAS 3D then creates global 3D synthetic temperature and salinity fields that become the background (first guess) field of the NCODA 3D MVOI.

The *in situ* temperature and salinity observations from gliders, buoys, etc. are processed by the NCODA OcnQC (section I-C). These correspond to the observation vector mentioned previously ($\mathbf{y}$ in the 3D MVOI equation). The background field produced by MODAS 3D ($\boldsymbol{H}(\mathbf{x}_b)$) is subtracted from these observations to produce the innovations that are transformed by the 3D MVOI into the output increment. These innovations are computed without the First Guess at Appropriate Time (FGAT) method of section III. This increment is added to the input background field to produce a 3D temperature and salinity field. GNCOM is relaxed to this field over a three day hindcast.

This global ocean prediction strategy [14] satisfies the need for ocean models to have a high horizontal resolution (required to successfully simulate the variability of mesoscale features) and a high vertical resolution (required near the surface to resolve the physics of the upper ocean) [15]. This first generation global ocean prediction system meets these needs by combining GNLOM (for high horizontal resolution) and GNCOM (for high vertical resolution).

GNCOM produces forecasts of up to 72 hours. Its output is used as boundary and initial conditions for nesting the higher resolution RNCOM/NCODA system (to be discussed in section III) inside of it. Since GNCOM does not include tides, these are introduced from an external tidal database when GNCOM is coupled with a nested RNCOM/NCODA system.

III. NCODA Coupled with RNCOM

The Regional Navy Coastal Ocean Model (RNCOM) [16] is the Navy's choice for high resolution applications. It is based on the Princeton Ocean Model [17], combining Sigma–layers and Z–levels [18], permitting use of a hybrid vertical coordinate system [15]. The vertical grid is set up to offer a choice of Sigma–layers or Z–levels, or some combination with Sigma–layers in the shallow water and Z–levels in the deeper water. A typical implementation of RNCOM may be at 1/32 or 1/64 degree resolution, with 45 levels (15 Sigma–layers and 30 Z–levels), and forecasts from 72 to 96 hours. The model is forced with the high resolution regional Coupled Ocean Atmosphere Mesoscale Prediction System (COAMPS) [19].

RNCOM takes its boundary conditions (BC) from GNCOM. Since GNCOM does not include tides, they are introduced by adding tidal heights and transports to the BC (from the Oregon State University tide model [20]). Internal to an RNCOM domain, tidal forcing is done via the tidal potential.

NCODA is the data assimilation system used by RNCOM. The data flow of the RNCOM/NCODA system was shown in figure 1 of section I-A. All of the raw observations pass through the NCODA OcnQC system as detailed in section I-C. With RNCOM the innovations are computed using the forecast from yesterday that is closest in time to the observation (the First Guess at Appropriate Time (FGAT) method). The background (first guess) field of the MVOI is the 24–hour forecast from yesterday. The temperature and salinity increment fields produced by the 3D MVOI are what is used by RNCOM (in contrast to GNCOM).

In order to minimize spurious gravity waves (resulting from introducing an unbalanced increment into the model), the RNCOM/NCODA system uses an "incremental (analysis) updating" (or data insertion) method of assimilating the temperature and salinity increments (see figure 11). This is accomplished by a 24–hour hindcast that starts with yesterday's nowcast and gradually inserts the temperature and salinity increments. The velocity fields are allowed to adjust via geostrophy.

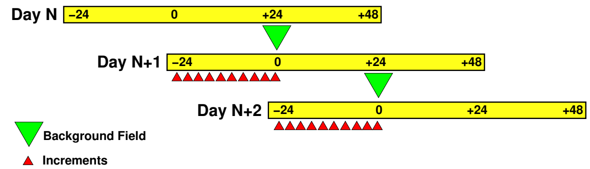

Fig. 11. The RNCOM/NCODA system uses an "incremental (analysis) updating" (or data insertion) method of assimilating the temperature (T) and salinity (S) increments. The T,S increments are gradually inserted during a 24–hour hindcast. This helps maintain dynamic balance and cut down on spurious gravity waves.

A. RNCOM/NCODA Metrics

The performance of the RNCOM/NCODA system can be monitored by several graphics. In figure 12 are shown profile plots of the temperature fields from the *in situ* observation (Obs), NCODA analysis (Anal), RNCOM nowcast (NCST) for today, RNCOM 24–hour forecast (FCST) from yesterday, GDEM climatology (Clim), and the background field (BG) with its associated error (E). Recall that the NCODA analysis increment is passed to the RNCOM model, which gradually inserts it over a 24–hour hindcast to produce the nowcast for today. The background field (BG) is the FGAT field used when computing the innovation for input to the analysis. Figure 13 is an anomaly plot of the same quantities with respect to the *in situ* observation. Note that in the anomaly plot the "background anomaly" is actually the "innovation", which is used by the analysis with appropriate weighting based on its probability of error values.

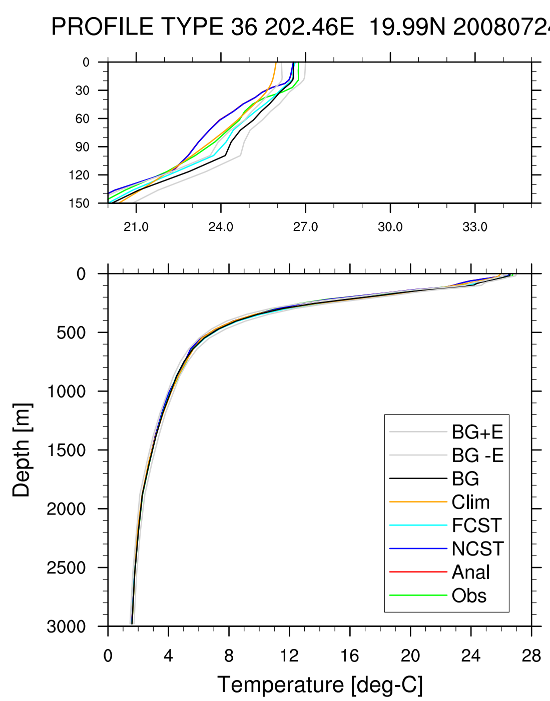

Fig. 12. Profile plots of the temperature fields from the *in situ* observation, NCODA analysis, and the RNCOM nowcast and forecast.

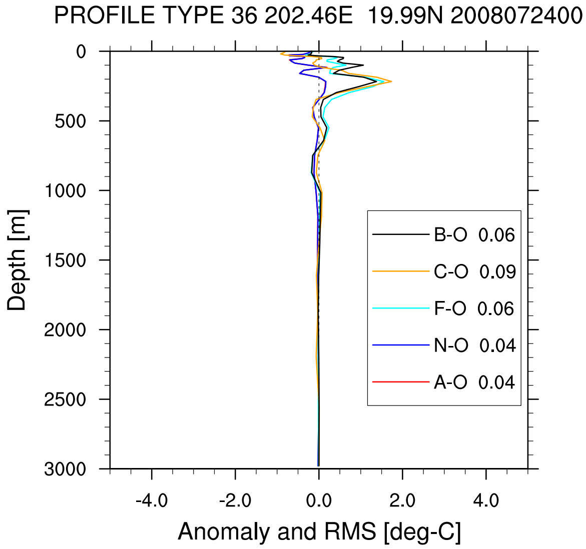

Fig. 13. Profile plots of the anomaly fields (difference from the *in situ* observation) from (1) the NCODA analysis and (2) the RNCOM nowcast and forecast. Overall RMS values are shown within the legend. Note that the background anomaly (B–O) is the innovation computed using FGAT. In general the analysis should have the best fit to the data, but the nowcast should have the best dynamical balance.

How well the system is removing any bias and reducing the root–mean–square (RMS) variability is also monitored. Scatter plots are made showing the results before and after the analysis, which correspond to the statistics of the innovations (before) and the statistics of the residuals (after). Figure 14 is an example of a regional SST analysis where a large bias was corrected and the RMS was significantly reduced. An example of tracking the regional RMS–at–depth over time is shown in figure 15. In this case for the Hawaii region, the RMS signals seem to contain a 48–hour signal, with the largest RMS values occurring at depths where the internal tides have the most effect.

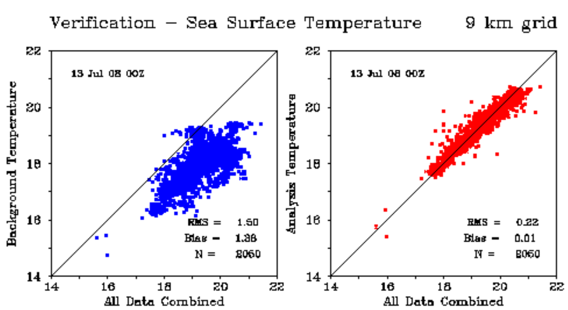

Fig. 14. Scatter plots of matchup statistics before (blue) and after (red) the NCODA Analysis.

IV. RNCOM/NCODA Ensembles and ASAP

Recall in section I-D that NCODA is able to introduce flow–dependence into the data assimilation by means of a flow–dependent correlation (C_f). An improved method

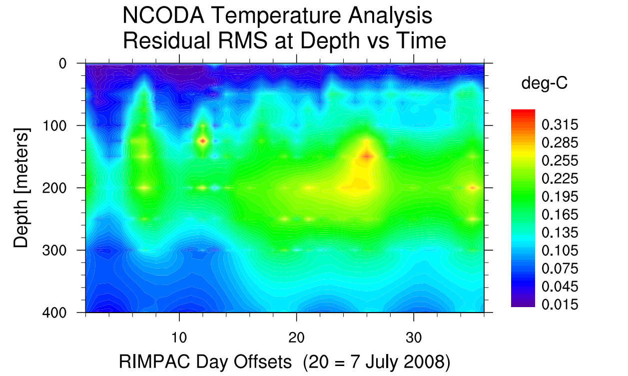

Fig. 15. The residual RMS of the NCODA temperature analysis over time (as a regional average) is studied. The residual RMS is largest between 100 and 300 meters in this region around Hawaii, with maximum variations likely occurring where internal tides have the most effect.

of determining the flow–dependence is to have an ensemble of ocean model runs valid at the same times. This will allow a better estimation of the background error (variance).

The results of ensemble forecast runs will not only give better estimates of background errors, but can also provide estimates of future errors (in sound speed variability, etc.), which can be used to predict where observations should be taken now in order to reduce those errors. This is important when the Navy must decide how and when to deploy a limited number of assets in order to attain a better knowledge of the battlespace environment.

To accomplish this, the RNCOM/NCODA system is being used as part of an Adaptive Sampling and Prediction (ASAP) project that makes use of the Ensemble Transform (ET) and Ensemble Transform Kalman Filter (ET KF) applied to ensemble runs of the RNCOM.

Letting ϵ represent the error (uncertainty) in a quantity, the error in a RNCOM forecast may be represented as follows:

$$\epsilon_{Forecast} = \epsilon_{Forcing} + \epsilon_{IC} + \overbrace{\epsilon_{BC} + \epsilon_{Model} + \epsilon_{Turbulence}}^{\text{Not Yet Included}}$$

There are other terms that could be included, such as errors in the bathymetry and sub–grid variability. Only the first two sources of error are implemented at this time. Thus, the ensemble generation for RNCOM/NCODA is done by perturbing the forcing and initial conditions.

Perturbation of the forcing takes the form of a space–time deformation of the atmospheric forcing [21]. This results in an ensemble of atmospheric states – an independent atmospheric forcing for each RNCOM ensemble member.

Perturbation of the initial conditions (IC) is done by the Ensemble Transform (ET) technique [22] [23]. The ET method uses the best available estimate of analysis error covariance to transform forecast perturbations into analysis perturbations by finding K distinct linear combinations of K forecast perturbations that (1) are equally likely, (2) lie within the vector subspace of forecast perturbations, (3) are quasi–orthogonal (although they sum to zero), and (4) have expected squared amplitudes equal to the trace of the best available estimate of the analysis error covariance matrix. For the current work, the best available estimate of the analysis error covariance is obtained from the NCODA analysis error.

The K perturbations to the IC are then added to the RNCOM control run to produce K initial states. These K initial states (ensemble members) are then integrated forward in time with their respective atmospheric forcings to produce K forecasts. These forecasts are used with the ET KF technique for ASAP purposes [24]. At this point the process can be restarted for the next ASAP run.

The use of the RNCOM/NCODA system for ASAP has been done for several ocean measurement exercises [25] [26] [27] [28]. To make the ability to perform ASAP and adjust the parameters it uses more accessible to the warfighter, a software system called "Targeted Observations for Forecast Uncertainty (TOFU)" has been developed [25] [27]. It creates metrics that can be used for ASAP, and that also assess how well the ASAP is performing.

The TOFU system produces "Target Observations Summary (TOSum)" maps as shown in figure 16. These display the relative impact of each possible temperature–salinity profile observation in reducing the predicted errors of a set of target variables (such as sonic layer depth and below layer gradient) over a user–specified target area and for a given target forecast time. These maps can then be integrated with other criteria to optimally design, deploy, and update local observation networks that will provide the best accuracy of ocean dynamic inputs into end user applications.

In the case of figure 16, the red box outlines the target area. There are four gliders, with three within the target area. The possible deployments of each glider (taking account of ocean currents) are shown by white lines. Red areas on the map indicate locations where measurements will have a large relative impact on reducing the forecast error (uncertainty) within the target region. Blue areas will have a small impact.

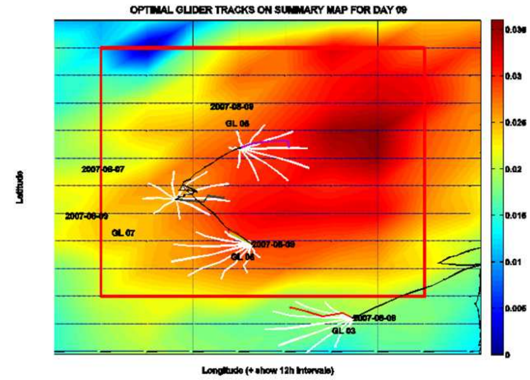

Fig. 16. TOSum map for three gliders, showing possible deployments of the gliders and the relative impact of each upon the target area (red box).

V. Future NCODA Enhancements

The data assimilation algorithm used by NCODA is being updated in several stages. The first transition will be to a 3D variational (3DVar) approach [29]. The equation to be solved is the same as the one given in section I-D, but using variational techniques. The techniques will come from the NRL Atmospheric Variational Data Assimilation System (NAVDAS), which is an observation–space based 3DVar system for generating atmospheric state estimates. NAVDAS permits the direct assimilation of satellite radiances, which have resulted in significant forecast improvements at other forecast centers [30].

The next transition will be to a 4D variational (4DVar) approach [31] applied to the RNCOM model [32]. This 4DVar approach will be based upon the "Cycling Representer Method". In this method RNCOM is linearized about a background state using tangent linearization. The stability of this tangent linearized model (TLM) is a very sensitive function of the background state, the level of nonlinearity of the model, open boundary conditions, and the complexity of the bathymetry and flow field. Based on the TLM stability time period, the Representer Method is cycled by splitting the time period of the assimilation problem into short intervals. The interval time period needs to be such that it is short enough for the TLM to be stable, but long enough to minimize the loss of information due to reducing the temporal correlation of the dynamics and data.

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